

Who Cares What Others Think (or Do)? Social Learning and Social Pressures in Cotton Farming in India

Annemie Maertens*

Keywords: Agricultural Technology Adoption, India, Social Learning, Social Pressures

JEL Codes: O3, Q1

June 2016

*University of Sussex. E-mail: A.Maertens@sussex.ac.uk. This research was funded through a NSF Doctoral Dissertation Research Improvement Grant (Grant No. 0649330), an AAEA McCorkle Fellowship, a Mario Einaudi Center for International Studies International Research Travel Grant, a Cornell University Graduate School Research Travel Grant and an International Student and Scholar Office Grant. I am grateful towards ICRISAT, AIIS, ISI and Chris Barrett for additional logistical and financial support and field RAs assistants: Sanjit Anilesh, Shraavya Bhagavatula, Pramod Bangar, Sana Butool, V.D. Duche, Shital Duche, Madhav Dhere, Anand Dhumale, Meenal Inamdar, Shilpa Indrakanti, Navika Harshe, Sapna Kale, Jessica Lebo, Labhesh Lithikar, Nishita Medha, Ramesh Babu Para, Abhijit Patnaik, Gore Parmeshwar, Amidala Sidappa, Nandavaram Ramakrishna, K. Ramanareddy, P.D. Ranganath, Arjun Waghmode and Yu Qin. I have benefited considerably from discussions with Cynthia Bantilan, Chris Barrett, Kaushik Basu, Marc Bellemare, Larry Blume, Sommarat Chantarat, A.V. Chari, V.K. Chopde, Stephen Coate, Vincenzo Di Maro, Ronald Herring, George Jakubson, Fernanda Leite Lopez DeLeon, Jack Meyer, Felix Naschold, K.P.C. Rao, Mohan Rao, Nageswara Rao, Paulo Santos, Russell Toth, Kumar Acharya Ulu, Alex Yuskavage and the comments of seminar participants at the University of Madison-Wisconsin, ISI, Johns Hopkins University, Toulouse School of

Abstract

This article examines the role of social networks in the adoption process of Bt cotton, a new type of (genetically engineered) cotton available on the Indian market since 2002. Using a unique dataset and empirical methodology, I find that farmers appeared to have exclusively learned from the experimentation of a small set of "progressive" farmers in the village, i.e. adoption by other ("regular") farmers was not regarded as a useful source of information about the technology. Second, I find evidence of social pressures, originating from the belief that Bt cotton might be hazardous to the environment and livestock, which inhibited adoption (for at least some time).

New agricultural technologies in developing countries have the potential to significantly increase agricultural incomes and living standards, thereby transforming the rural economy. However, when these technologies are introduced, adoption often does not occur immediately. Farmers instead appear to follow a complex pattern of gradual adoption, dis-adoption and often non-adoption (Besley and Case 1993, Feder, Just and Zilberman 1985, Sunding and Zilberman 2001).

What determines the pattern of adoption? The literature has emphasized the role of prices, attributes of the individual (such as income, risk-aversion, education, etc.), and attributes of the technology as important predictors of adoption behavior (see Feder, Just and Zilberman 1985 for an overview). However, as Griliches (1957) and Rogers (1962, 1995) note, these technological attributes need to be known by the farmer in order to influence

Economics, University of Maryland, Amherst College, Simon Fraser University, Stanford University, University of Pittsburgh. Any remaining errors and omissions are my own.

his behavior. In the absence of such information, a certain amount of experimentation is required on the part of the farmer before he can establish the profitability of the new technology. By itself, this poses a constraint to adoption. More recently, the literature on technology adoption has emphasized the importance of social learning, whereby farmers learn from the experimentation of others (see Bandiera and Rasul 2006, Conley and Udry 2010, Foster and Rosenzweig 1995, McNiven and Gilligan 2012, Munshi 2004). Whether, and at what rate, such diffusion increases adoption depends on (a) the incentive of individuals to strategically delay adoption (and free-ride on the experimentation of others)¹ and (b) on the structure of the social network.

The recent literature on technology adoption has indeed found evidence of strategic delaying behavior (see Bandiera and Rasul 2006, Foster and Rosenzweig 1995). We know relatively little, though, about how the structure of social networks influences adoption. If social relationships are structured such that everyone learns from a few key figures, the outcome may be perverse: the inherent stochasticity of returns, combined with experimentation by a select few (on whom the others in the village are dependent on for information), may result in little to no adoption (this insight is formalized in Bala and Goyal 1998).

While experimentation by an individual farmer creates externalities through the social learning process, there is an additional, distinct source of externality that arises from the nature of new agricultural technologies. The introduction of new Genetically Modified Organisms (GMOs) is responsible for a large share of the technological progress in agriculture. There is a lively debate on GM technologies in Europe and much of the developing world. While new technologies might be generally viewed with suspicion, GM technologies are, in addition, often (correctly or incorrectly) associated with harmful externalities

(in terms of consumers' and farmers' health and the environment). Where new technologies are identified with negative externalities, social pressures may inhibit the adoption process (Appadurai 1989, Moser and Barrett 2006, Rogers 1962, Vasavi 1994). By inhibiting adoption (and hence experimentation), these pressures can also reduce the amount of information generated about the technology.

Using a unique household-level dataset I collected for this purpose in three villages in rural India, this article studies the adoption process of *Bacillus thuringiensis* (Bt) cotton, a new type of cotton introduced in India that requires fewer pesticides and can increase expected yields (see, among others, Kathage and Qaim 2012, Klumper and Qaim 2014, Qaim 2003, Qaim and Zilberman 2003, Qiao 2015).

Qualitative evidence points to the existence of a hierarchical learning structure in these villages, in which a few important farmers in the village (following Rogers 1995, I will henceforth refer to them as "progressive farmers") are early adopters and are one of the primary sources of information about the new technology (see also Feder and Savastano 2006 on the role of leaders). In addition, there is reason to believe that social pressures are important in the adoption process because of the commonly-held (but erroneous) belief that the cultivation of Bt cotton, a GM crop, is harmful to animals (as well as to humans and the environment). This combination of social pressures and reliance on experimentation by progressive farmers appears to have given rise to rather diverse patterns of adoption in the sample villages.

Disentangling the effects of social learning and social pressures on adoption is important from a policy perspective, but encounters significant challenges in practice. Obtaining an accurate picture of an individual's social network from the information contained in

a limited sample is not straightforward (for example Foster and Rosenzweig 1995 simply take the village to be the relevant social group, although Bandiera and Rasul 2006 and Conley and Udry 2010 explicitly measure social networks), and existing methods of doing so are not without pitfalls. In particular, surveys which sample the social network without regard to hierarchical structure may misstate the nature of learning by failing to capture the central nodes in the diffusion process, which produces spurious correlations in the actions of farmers which are then interpreted causally. Even if social networks are well-measured, there remains the thorny issue of inferring causal social interaction effects from correlations in individuals' behavior (see Manski 1993 for the identification challenges in a linear-in-means model). Constraints such as soil and climatic conditions, which can coordinate the actions of individuals, are rarely recorded in detail (Conley and Udry 2010 is a notable exception). Individual attributes such as risk aversion (also typically unobservable) can influence the network formation process as well as adoption behavior. Finally, because different kinds of social interaction effects all result in correlation between individual and group behavior, it is difficult to disentangle their separate influences.

The data collection was specifically geared to address these empirical challenges. I elicited detailed information on farmer networks, distinguishing between the *learning network*, defined as those network neighbors of the farmer whose choice of technology (in this case, the cultivar), inputs and outputs are known to the farmer, and the *non-learning network*, defined as network neighbors for whom the farmer only knows the choice of technology. I also ensured that links to progressive farmers were elicited for each farmer. A second unique feature of the data collection was the elicitation of farmers' current beliefs regarding the profitability of Bt and non-Bt cotton. Third, I elicited farmers' perceptions of

the biosafety of Bt cotton, as well as their perception of the concerns of others in the village. Last, but not least, I collected plot, household and village level information resulting in a detailed dataset on the agro-climate, agricultural production, prices, income, risk attitudes and wealth, in order to control for potentially confounding (non-social) factors that might correlate farmers' actions.

The direct elicitation of beliefs and the elicitation of detailed network information are key innovations of the data collection that allow me to distinguish the channels of social interaction. I examine how a farmer's adoption decision is affected by the expected adoption decisions of other farmers in his network. Conditional on the farmer's beliefs about the yield of Bt cotton, the adoption decisions of others do not signal any new information about the technology; instead, their decisions matter only because of strategic considerations. These considerations relate to the possibility of strategically delaying adoption (and free-riding) on others' future experimentation, and to the strength of social pressures (because social pressures are likely related to the overall rate of adoption of the new technology). I distinguish between these two effects empirically by relying on the distinction between learning and non-learning networks: Strategically delaying behavior should only be a response to the adoption plans of those in the farmer's learning network, whereas the strength of social pressures plausibly depends on the adoption behavior of all farmers. I supplement this analysis with an analysis that uses adoption histories over a seven-year period preceding the survey, to examine how a farmer's adoption decision at a point in time relates to the contemporaneous and past adoption decisions of other farmers.

The results provide a nuanced picture. First, (conditional on their beliefs about the technology) farmers are more likely to adopt Bt cotton if there are many others in the vil-

SOCIAL LEARNING AND SOCIAL PRESSURES IN COTTON FARMING

lage who are also doing so, indicating the presence of social pressures. There is also clear evidence of social learning, but not all sources of information are equal. Specifically, I find evidence of farmers free-riding on the experimentation of the progressive farmers, delaying their adoption when they know more progressive farmers who are currently adopting. However, there is little evidence that farmers learn from the experimentation of non-progressive farmers. This finding is significant because local information (i.e. information derived from one's immediate neighbors) is an important factor that can support the spread of a beneficial action, and can counteract the effects of bad information derived from central sources (Bala and Goyal 1998, Goyal 2005). The lack of importance given to local information (at least in these villages) therefore has the potential to exacerbate the learning externalities generated by the experiences of a few key farmers in the village, giving the latter an outsized influence on the overall rate of adoption.

Bt Cotton in India

Cotton is one of the main cash crops in India. In the late 90s and early 2000s, cotton yields in India were low, averaging only one third of China's yield (USDA, 2016). Losses in cotton production were attributed to its predominant rainfed cultivation and susceptibility to insects, pests and diseases (and in particular bollworms). In the 2005, nearly 50% of pesticides used in India were used on cotton (ISAAA 2005). As a response to the bollworm pest problem, Monsanto, a US agricultural company, developed the Bt genetically modified technology during the 1980s. In collaboration with the Maharashtra Hybrid Seed Company (Mahyco), the technology was then introduced into several of Mahyco's breeding lines during the 1990s.² In 2002, the Genetic Engineering Approval Committee (GEAC), an Indian government body, approved the commercial release of three Bt cotton cultivars

of Mahyco. At the time of the survey, in 2008, 225 Bt cotton cultivars had been approved by GEAC. In 2015, 1,128 Bt cotton cultivars were on the Indian market. Government regulation and competition in this sector resulted in a drop in Bt cotton seed prices, from over 1600 Rs per packet (450 g of Bt cotton seeds and 120 g of refugia non-Bt cotton seed, sufficient for one acre of land) in 2002 to 650-750 Rs per bag in 2008. The 2016 price stands at 635 Rs per packet.³

Since its introduction in India, the Bt technology has been surrounded by controversy and debate largely centered around biosafety of genetically modified crops. These biosafety concerns may lead to social pressures that inhibit the adoption of Bt cotton (especially in the early years of the technology), i.e., a farmer might be accused of endangering the health of animals and people in the village as well as generating negative impacts on the soil fertility and water quality of neighboring plots. The scientific evidence available to date has shown that Bt cotton poses no significant risk to the environment or human and (vertebrate) animal health (see, among others, Mendelsohn et al. 2005, Shelton, Zhao and Roush 2002). In effect, environment and human health are likely to benefit from reduced pesticide use (Abedullah, Kouser and Qaim 2015, Kouser and Qaim 2011). The longer term landscape-level effects on non-target organisms, and the degree of pest resistance, however continue to be subject to study (Lu et al. 2010, Lu et al. 2012, Marvier et al. 2007, Tabashnik, Brévault and Carrière 2013).

In terms of yields and profits, Kathage and Qaim (2012), using panel data collected between 2002 and 2008 among 533 farm households in central and southern India, conclude that Bt cotton has caused a 24% increase in cotton yield per acre and a 50% increase in profits among smallholders. Agricultural field trials confirm this conclusion: Qaim and

Zilberman (2003) analyze trials from 2001-02 (a high bollworm pressure) on Bt cotton and its isogenic non-Bt counterpart and find that, independent of soil and climatic conditions, profits from Bt cotton are higher than profits from non-Bt cotton.⁴ In the three villages I consider in this article, Aurepalle in the Mahbubnagar district in Andhra Pradesh and Kan-zara and Kinkhed in the Akola district in Maharashtra, profits from Bt cotton are higher than profits from non-Bt cotton, irrespective of bollworm pressure, soil and climatic conditions, during 2006-2008 (see supplementary appendix online).

Conceptual Framework

I first formalize the determinants of adoption. Denote by $y_{i,t}$ the cultivation decision of farmer i : Thus $y_{i,t} = 1$ if farmer i plans to cultivate Bt cotton in period t , and $y_{i,t} = 0$ if the farmer plans to cultivate non-Bt cotton. I model $y_{i,t}$ as a function of farmer i 's beliefs about the yield of Bt cotton, his expectations about the actions of other farmers, and his perception of others' safety concerns regarding Bt cotton:

$$y_{i,t} = f(\Omega_{it}, s_{-i,t}, s_{it}, \mathbf{y}_{-i,t}^e, \mathbf{X}_{it}) \quad (1)$$

where Ω_{it} denotes farmer i 's beliefs about the yield of Bt cotton, s_{it} denotes his own biosafety concerns and $s_{-i,t}$ denotes his perception of the biosafety concerns of others, $\mathbf{y}_{-i,t}^e$ is a vector that denotes (farmer i 's belief about) the cultivation decisions of other farmers, and \mathbf{X}_{it} denotes a vector of characteristics of farmer i at time t . The latter includes the farmer's risk-aversion, credit constraints, and prices. I now discuss each of the first four elements in turn.

The farmer's beliefs about the yield of Bt cotton, Ω_{it} , are shaped by his own priors, the information he has obtained from his own past experimentation, and the information

obtained from others' experimentation. Indeed, by observing the outcome of the experimentation by farmers in his learning network, the farmer can update his beliefs about the profitability of the technology. However, the farmer may also revise his beliefs to take into account the fact that farmers in his non-learning network have adopted the technology, even though he cannot observe their yields, because their behavior constitutes a (noisy) signal about the profitability of the technology. For the same reason, contemporaneous adoption by other farmers is also incorporated in Ω_{it} , even though the outcomes of these experiments are yet to be known. Lastly, an important feature of the perceived yield distribution Ω_{it} is that it incorporates the technological constraints faced by farmer i , including soil conditions and water availability.

The farmer's beliefs about the biosafety of Bt cotton, denoted by s_{it} , as well as his perception about others' concerns about Bt cotton, denoted by $s_{-i,t}$, also influence his adoption behavior. In particular, $s_{-i,t}$ directly relates to social pressures: If (he thinks that) others are concerned about potential negative externalities from Bt cultivation, this may discourage the farmer from adopting it himself for fear of social sanctions. Both s_{it} and $s_{-i,t}$ may be shaped by the past and current adoption behavior of others in his network. For instance, current adoption by others in his network may signal to the farmer that the technology is safe, and may cause him to revise s_{it} .

The fourth determinant of adoption, $\mathbf{y}_{-i,t}^e$, potentially arises from two considerations. The previous discussion implied that, conditional on Ω_{it} , s_{it} , $s_{-i,t}$, and \mathbf{X}_{it} the contemporaneous adoption plans of others, $\mathbf{y}_{-i,t}^e$, do not contain any new information about the profitability of the technology or its biosafety. Indeed, all information about profitability is embedded in Ω_{it} and \mathbf{X}_{it} , while own biosafety concerns are embedded in s_{it} . There are

however two reasons why $y_{-i,t}^e$ may nonetheless exert an independent influence on $y_{i,t}$: (1) farmer i may choose to strategically delay and free-ride on the experimentation of the current adopters in his network, implying that an increase in expected adoption in the network would tend to reduce the probability that farmer i adopts, and (2) the influence of social pressures (deriving from other villagers' safety concerns about Bt cotton) may depend on the extent of adoption of Bt cotton: For instance, an individual Bt farmer is less likely to be blamed for any occurrences of human or animal illness in the area if he is only one among many Bt cultivators, implying that an increase in the expected number of adopters would tend to increase the probability that farmer i adopts. In the context of strategically delaying behavior, it is important to note that the farmer could only hope to learn from the experimentation of farmers whose yield he can observe, i.e. those farmers who are in his learning network. In the case of social pressures, however, what matters is the total number of expected adopters, regardless of whether the adopters are in farmer i 's learning network or in his non-learning network. This is a key distinction that will allow me to distinguish the effect of free-riding from that of social pressures. Specifically, adoption in the farmer's learning network should have a negative effect on his adoption probability, relative to adoption in the non-learning network, because the former activates the strategically delaying channel in addition to the social pressure channel.

Lastly, note that although the technological factors that determine yield and hence adoption, such as soil characteristics and irrigation, are assumed to be embedded in Ω_{it} , the adoption decision is also likely to be influenced by factors such as the farmer's risk-aversion, credit constraints, and prices which are included in the vector X_{it} .

Data Collection

I use two sources of data for this study: Data from an existing ICRISAT- VLS survey, and data from a survey I collected for the purpose of this study in the same villages. As part of its Village Level Studies (VLS) program, ICRISAT annually surveys households in rural India (Bantilan et al. 2006 and Rao and Charyulu 2007). The VLS villages were selected in 1975 as to represent (albeit not statistically) the semi-arid tropics in India (Walker and Ryan 1990). Of the ICRISAT-VLS data, I use the 2001-2008 modules on agricultural inputs, outputs, prices and household wealth.

In addition, I resurveyed 246 ICRISAT-VLS households in the villages of Aurepalle, Kanzara and Kinkhed in 2008 (for information on survey attrition between 2001 and 2008, see the supplementary appendix online). Aurepalle, with 925 households, is the largest of the three villages. It is located in the drought-prone, poor, Telangana region of Andhra Pradesh and in terms of average income situated between the richer Kanzara and poorer Kinkhed. Kanzara and Kinkhed, with respectively 319 and 189 households, are located in the Akola district of West Maharashtra. The ICRISAT-VLS sample includes 128, 63 and 55 households in Aurepalle, Kanzara and Kinkhed, respectively. The majority of the farmers in the village cultivate cotton; it is these cotton farmers which are the focus of the analysis. For instance, in 2008, there were 130 farmers who were planning to cultivate cotton in 2008-09. These represent the sample for the cross sectional analysis.

I elicited each farmer's cultivation decisions for the forthcoming cropping season 2008-09 (elicited in the month that seeds had to be bought so as to accurately reflect planned cultivation choices), as well as recall information on past cotton production decisions covering the period 2001-08. I also included questions on household composition, landholding, wealth, credit⁵ and irrigation constraints, risk preferences⁶ and per-plot agricultural

SOCIAL LEARNING AND SOCIAL PRESSURES IN COTTON FARMING

inputs and outputs (all pertaining to the time of survey).

To analyze the role of social networks in the adoption process of Bt cotton, the survey included modules for measuring social networks and beliefs about the yield and biosafety of Bt cotton. These parts of the survey have some important elements that I describe below.

Identifying Key Farmers

According to the village farmers' own account in a qualitative survey preceding the data collection, certain individuals in the village act as early adopters of new technologies, and appear to play a central role in the diffusion of information. I identified a set of "progressive farmers" based on group discussions with the junior VLS investigators who have been living in the village since 2001, the senior VLS investigators who have known the villagers since the beginning of the VLS survey in 1975, and village elderly. The pre-identification of the progressive farmers took place during a separate visit in between the qualitative data collection and the pilot testing of the questionnaire. During this conversation, I did not mention that the topic of the study was Bt cotton; instead, I spoke in general terms of technology leaders in the village. We then had a focus group discussion with 5-6 members in each village as well as the live-in enumerators, using social network graph tools. Of the 43 progressive farmers thus identified (28 in Aurepalle, 6 in Kanzara and 9 in Kinkhed), 21 were outside the ICRISAT-VLS sample. The data provide confirmation that this initial identification of progressive farmers as technology leaders was valid: When asked "If you, today, would have a specific problem with your cotton crop, who or where would you go to (up to 5 answers allowed)?", 63%, 78% and 85% of the responses in Kanzara, Kinkhed and Aurepalle, respectively, matched a pre-identified progressive farmer.

Measuring Networks

SOCIAL LEARNING AND SOCIAL PRESSURES IN COTTON FARMING

I measured networks using the ‘random-matching-within-sample’ technique, based on Conley and Udry (2001, 2010) and Santos and Barrett (2007). Each respondent was matched with six randomly drawn VLS respondents as well as four pre-identified progressive farmers. I elicited the details of the relationship between the respondent and each match, particularly focusing on the knowledge that the respondent has about the match’s farming activities in terms of inputs and outputs in the current season. A particular match is only considered to be in the farmer’s network if the farmer knows (or, more precisely, thinks he knows) the match’s choice of cultivar. In the analysis, I further distinguish between ‘learning’ and ‘non-learning’ networks: A network contact is classified as being in farmer *i*’s learning network if farmer *i* knows (or more accurately, thinks he knows) the contact’s cultivar choice, pesticide use and yield, as knowledge of these would allow the farmer to infer the profitability of the technology being used by the contact. All other network members are classified as belonging to the farmer’s non-learning network, i.e. this is the complementary network. I also distinguish between progressive and non-progressive networks, the former being defined as the set of progressive farmers who are in farmer *i*’s network, and the latter consisting of all other farmers in his network.

In addition to learning from each other, farmers might receive information through (typically unannounced) visits of company agents to the village and conversations with the input dealers in the nearest urban hub. To capture these interactions, I added a module on the information obtained since 2001 from contacts with extension agents, NGOs, company agents, input dealers and ICRISAT.

Measuring Yield Beliefs

I elicited information on current beliefs regarding the profitability of Bt and non-Bt cotton

and the biosafety hazards associated with Bt cotton. I used an exercise based on Lybbert and Just (2007), in which respondents were asked to construct yield distributions for Bt and non-Bt cotton.⁷ I refer to these yield distributions as yield beliefs (see also, Delavande et al. 2010, 2011).

Measuring Biosafety Concerns

To elicit the respondent's biosafety concerns, I asked the respondent to what degree he/she thinks that Bt cotton is hazardous for (1) animal health, (2) for human health, (3) for the environment.⁸ As the qualitative survey preceding the data collection revealed that perceived biosafety concerns of others may also exert an effect on adoption behavior, I then repeated this question but this time referring to the beliefs of 'others in the village'.

Descriptive Statistics

Table 1 presents summary statistics on the composition of cotton farmers in the three study villages, differentiating between progressive and non-progressive farmers. To maintain a consistent sample, this section reports descriptive statistics on the 130 cotton farmers used in the cross sectional analysis pertaining to the 2008-2009 season. On average, the progressive farmers are more educated and own more land, of which a larger share is irrigated. It is also worth noting that there are large differences in the level of education between Aurepalle and the two villages in Maharashtra, Kanzara and Kinkhed.

Table 2 summarizes farmers' biosafety concerns (in 2008), averaging over the three types of concerns (relating to animal health, human health and the environment, respectively). Biosafety concerns differ between the study villages, with Aurepalle respondents being less concerned than farmers in Kanzara and Kinkhed. To further understand which elements of safety the farmers were concerned about, I plot the percentage distribution of

responses to the three types of questions in figure 1 in the supplementary appendix online. As the figure shows, concerns related to the biosafety of Bt cotton are generally very low in Aurepalle, but more widespread in Kanzara and Kinkhed, especially with regard to environment-related concerns.

Table 3 summarizes the yield beliefs (in 2008) for each of the Bt and non-Bt cultivars that the farmer was asked about. All respondents attributed a uni-modal yield distribution to all cultivars, and even though I reject normality for the sample as a whole (the yield distributions are, on average, left-skewed and platykurtic), they are close to normality. On average, Bt cotton cultivars are thought to have a higher expected yield than non-Bt cotton cultivars. In addition, progressive farmers expect a higher yield from Bt cotton than non-progressive farmers, although the difference in expected yield is only statistically significant for the first cultivar elicited (which is also most likely to be the cultivar that the farmer is most knowledgeable about). To compare these beliefs with actual yield realizations, Table 4 shows the average yields associated with Bt and non-Bt cotton in the 2006-2007 for the two groups of farmers.⁹ With the caveat that these yield data (part of the existing ICRISAT-VLS survey) are of poor quality, due to conversion issues with mixed cropping arrangements, we observe that progressive farmers appear to have obtained significantly greater yields per acre when cultivating Bt cotton than non-progressive farmers, although the differences in yield associated with non-Bt cotton are small and insignificant. In addition, the average Bt cotton yields exceed the average non-Bt yield yields across the board (this is consistent with Abedullah, Kouser and Qaim 2015 and Qaim and Zilberman 2012).

To examine how yield beliefs relate to actual yields, I conduct a simple regression

analysis (Table 5), regressing expected Bt cotton yield on farmer characteristics and past adoption and yield. As the results show, access to irrigation results in higher expected yield. There is also some evidence that educated farmers have lower yield expectations, suggesting that they may be less likely to overestimate the yield, while progressive farmers expect slightly higher yield. Once we control for prior adoption, the effects of these farmer characteristics shrink and become insignificant. It is reassuring to note that the prior adoption dummy has a large positive and statistically significant effect on expected yield. I also find that expected yields correlate strongly with actual yield and profits in 2006-2007 (the sample is now restricted to those farmers who cultivated Bt in 2006-2007, despite the fact that these variables are quite noisy).

Table 6 presents some descriptive statistics from the random-matching-within-sample method. Recall that each respondent drew 6 name cards of VLS respondents and was given a set of 4 fixed cards with names of progressive farmers. Farmers in Aurepalle, Kanzara and Kinkhed think they know the cultivar of 44%, 57% and 68%, respectively, of the 10 other farmers whose names they were shown. However farmers (think they) know the choice of inputs and output for a smaller set of individuals in the village, especially in Aurepalle and Kanzara, i.e. the learning network is, as is to be expected, smaller than the non-learning network. The learning network in Aurepalle, Kanzara and Kinkhed corresponds to, respectively, 17%, 22% and 55% of the 10 cards drawn. Some of these differences could be attributed to differences in village size: One can see that in a small village like Kinkhed, farmers appear to be informed about the activities and experiences of most other farmers in the village, but this is less so in a large village like Aurepalle. Maertens and Barrett (2013) used these data to estimate a dyadic regression to establish the corre-

lates of learning links. They find that belonging to the same sub-caste is associated with an increased likelihood of a learning link. Location matters as well: Living near another farmer, having a field near another farmer's field or merely passing by another farmer's field on a regular basis all increase the likelihood of a learning link. The difference between the farmer and his link's education, land acreage or age does not appear to be statistically significantly correlated with the probability of a learning link.

Bt cotton Adoption in the Study Villages: A Descriptive Account

To set the stage for the formal analysis, I briefly describe the adoption process in the study villages, drawing on the quantitative and qualitative parts of the survey. Figure 1 graphs the adoption rate of Bt cotton over time, separately for each of the three villages, distinguishing between adoption by progressive and non-progressive farmers.¹⁰ A common theme that emerged from the qualitative interviews was the central role played by progressive farmers as first adopters and sources of information about the technology. As figure 1 shows, in all three study villages, progressive farmers appear to adopt earlier than non-progressive farmers, and are (at time of survey) more likely to be cultivating Bt cotton.

There are also evident differences in the timing and rate of adoption between the study villages. This is partly due to the fact that in Andhra Pradesh, the state in which Aurepalle is situated, one out of three of the Bt cotton cultivars was not on the market during the first two cropping seasons (2002-04). In addition, during the first three years, NGOs and the Andhra Pradesh government challenged the decision of the GEAC with regard to the approval of Bt cotton, resulting in a discontinuation of the permission for commercial cultivation of several Mahyco cultivars in 2005. This legal battle and controversy around GM crops in the early years affected the farmers in Aurepalle as company agents did not ac-

SOCIAL LEARNING AND SOCIAL PRESSURES IN COTTON FARMING

tively promote the new Bt technology. Only one of the progressive farmers in Aurepalle learned about Bt cotton from non-farmer sources as early as 2002 and started to cultivate Bt cotton in 2003. The majority of the progressive farmers heard first about Bt cotton from the media and each other in 2003-2004 and the other cotton farmers heard about Bt cotton from the progressive farmers and company agents visiting the village in 2006-07. 91% of cotton farmers adopted Bt cotton in the same year that they heard about Bt cotton for the first time, displaying great confidence (by their own account) in the judgement of the progressive farmers and relying heavily on the advice of company agents and input dealers. No disadoption occurred in Aurepalle and only two farmers adopted the technology partially in 2006, cultivating both Bt and non-Bt cotton. The adoption rate at the time of survey in 2008 stood at 100%.

In Kanzara and Kinkhed, progressive farmers in the villages learned about Bt cotton from company agents, media and each other as early as 2001 and 2002, respectively. Nonetheless, adoption rates have been quite different in the two villages. In Kanzara, the Bt adoption process has been smooth, characterized by partial adoption, strategic delays and disadoption. Disadoption of Bt cotton is between 14% and 27% each year and the percentage of Bt farmers who are partial adopters ranges from 31% to 80%. The progressive farmers in the village started cultivation as early as 2002. The other village farmers heard about Bt cotton first from company agents, input dealers and progressive farmers. Most farmers, including the progressive farmers, did not adopt Bt cotton in the year that they first heard about it. The adoption rate at the time of the survey in 2008 stood at 54%. In Kinkhed, farmers appear to have adopted a 'wait and see' attitude, and as a result, the adoption process started only in 2006. The other village farmers heard first about Bt cotton

from input dealers, farmers outside of the village and the progressive farmers. The adoption rate at the time of the survey in 2008 stood at 14%. In fact, only one farmer classified as a non-progressive farmer had adopted the technology as of 2008.

What explains these different adoption processes? First, there are the usual constraints: credit, land and irrigation which are different across villages. Kanzara and Aurepalle farmers have a higher rate of access to credit from input dealers compared to Kinkhed which might have allowed them to start the adoption process when the price of Bt cotton was still high. Differences in landholding are also important because although the seed is inherently a scale-neutral technology, the fact that the seed needs to be bought in bags of one acre implies that farmers who own more land have more scope for experimentation. Irrigation is another important factor: Aurepalle farmers are exposed to a more drought-prone climate but typically have access to groundwater irrigation during the rainy season, while Kanzara and Kinkhed farmers, using surface water, do not. As groundwater is typically a more reliable source of irrigation than surface water and cotton is sensitive to lack of water, the latter might be more reluctant to switch to a high-input high-output technology.

To these constraints, one must add informational constraints. For instance, differences in access to the media (17% of Aurepalle farmers claims to have heard about Bt cotton from the media, versus 5% in Kanzara and 7% in Kinkhed (these differences are statistically significant at the 5% level between states) and differences in access to input dealers and company agents result not only in different beliefs with regard to the profitability of Bt cotton but also different beliefs with regard to its biosafety. But not all sources of information are external to the village. The experimentation and experiences of others in

the village constitutes a potentially important source of information about the technology. The extent to which farmers are connected to and can learn from the experiences of others farmers is quite variable. For instance, the average Aurepalle farmer, by sheer virtue of living in a larger village, might appear to have more opportunities to learn by observing other farmers' experimentation. However, as he only knows a small share of these villagers in a profound manner, i.e., by cultivar, yield and pesticide use, he is less likely to learn something useful from the Bt cotton farmers he knows. Further, the ability to learn from others' experimentation is limited by social pressures arising from biosafety concerns which reduce the total information available about the technology by inhibiting adoption by others. Last, but not least, an important theme that emerged in the qualitative interviews was the central role played by progressive farmers as first adopters and sources of information about the technology. This clearly has the potential to generate significant variation in adoption across the study villages, given the differences in rates of progressive farmer adoption of Bt cotton across these villages. Understanding these social interaction effects is the main objective of this article.

Analysis and Results

I first explore the data on adoption over the 2001-2007 period. I relate each farmer's adoption decision at each point in time to the current and past adoption decisions of farmers in his network. Past adoption in the network potentially matters for the farmer's current adoption decision because it shapes the farmer's current beliefs about the profitability of the new technology. Current adoption in the network may matter because it (in addition) might trigger strategic delays and/or moderate social pressures that inhibit adoption. Because the farmers' elicited beliefs about the yield of Bt cotton correspond only to the time

of survey (i.e. 2008), I cannot control for beliefs in this part of the analysis.

I first estimate the following probit model:

$$P(y_{i,t} = 1) = \Phi(\alpha + \beta n_{i,t} + \gamma n_{i,-t} + \delta \mathbf{X}_{i,t} + \eta_t + \epsilon_{it}) \quad (2)$$

where $n_{i,t}$ denotes the expected number of adopters of Bt cotton in farmer i 's network in the current period (i.e. $n_{i,t} = \sum_{-i} y_{-i,t}$), $n_{i,-t}$ denotes the number of times that Bt cotton has been cultivated in farmer i 's network in all past periods leading up to t (i.e. $n_{i,-t} = \sum_{-i} \sum_{\tau=1}^{t-1} y_{-i,\tau}$), η_t denotes a year fixed effect and $\mathbf{X}_{i,t}$ includes the remainder of the variables which are known to affect technology adoption, such as, information received from non-farmer sources (e.g., seed dealers), the farmer's subjective risk assessment, education level of the decision maker, assets, credit constraints, soil fertility and irrigation constraints, prices and village fixed effects. This wide range of controls, many of which are usually unobservable, limits potential omitted variable bias, including the bias associated with network formation along certain household and individual characteristics.

The regression sample retains each farmer only up to his first adoption of Bt cotton.¹¹ In this specification, the coefficient β reflects the effect of total contemporaneous adoption in farmer i 's network, while γ captures the effect of cumulative past adoption in the network. Recognizing the limitation in interpreting γ (see discussion below), I particularly focus on β whose sign is theoretically ambiguous, because current adoption in the network exerts a positive effect on farmer i because social pressures decline with increasing adoption, but at the same time exerts a negative effect to the extent that the farmer could free-ride on the experimentation of others in his network.

Column 1 of Table 7 presents the average marginal effects from regression (2). Con-

contemporaneous adoption in the network increases the probability of adoption by farmer i (each extra adopter in the network increases farmer i 's probability of adoption by 0.1 percentage points). Next, I refine the specification by distinguishing between adoption in farmer i 's progressive and non-progressive networks. The results are reported in column 2 of Table 7 (where the superscripts PF and nPF denote progressive and non-progressive farmer networks respectively). We now observe a sharp distinction between the effect of contemporaneous adoption by progressive and non-progressive farmers. Increased adoption in the current period by progressive farmers reduces the probability that farmer i adopts, whereas increased adoption by non-progressive farmers increases his probability of adoption. This dichotomy is consistent with the idea that farmers strategically delay adoption to observe the experimentation of progressive farmers, whereas contemporaneous adoption by non-progressive farmers works mainly through the social pressure channel, and therefore exerts a positive effect on adoption.

Next, I distinguish between adoption in learning and non-learning networks. We expect that strategic delay should only occur on current adoption behavior in the learning network while adoption behavior of non-learning network members should affect farmer i 's decision positively through the social pressure channel, implying that β^L should be less than β^{nL} . This hypothesis is supported by the results in column 3 (where superscripts L and nL denote learning and non-learning networks respectively) which indicate that $\beta^L - \beta^{nL}$ is negative and statistically significant at the 10% level: The strategic delay effect implies that an extra adopter in the learning network reduces the farmer's probability of adoption by 0.1 percentage points (the difference $\beta^L - \beta^{nL}$ reported at the bottom of Table 7).

Finally, I consider the most detailed specification which distinguishes between both progressive and non-progressive networks as well as between learning and non-learning networks. The results are reported in column 4 of Table 7. We see that within the progressive farmer network, adoption in the learning network has a negative effect relative to adoption in the non-learning network, i.e. $\beta^{PF,L} - \beta^{PF,nL} < 0$, consistent with farmers delaying adoption and free-riding on the experimentation of progressive farmers in their learning network. The free-riding effect is larger than that obtained in the specification in column (3) where we did not distinguish between progressive and non-progressive farmers: An extra adopter in the progressive-farmer learning network reduces the farmer's probability of adoption by 0.9 percentage points (the difference $\beta^{PF,L} - \beta^{PF,nL}$ reported at the bottom of Table 7). Interestingly, however, we do not find a similar effect when we look at adoption within the non-progressive farmer network - indeed, adoption in both the learning and non-learning networks has a positive effect, with the difference $\beta^{nPF,L} - \beta^{nPF,nL}$ being small and not significantly different from zero, suggesting that experimentation by non-progressive farmers is not an important source of learning about the technology and therefore does not give rise to strategic delays.

Although the results are suggestive, the methodology above has some important limitations. First, cumulative past adoption in the network is at best a weak proxy for the farmer's current belief about Bt cotton because the former does not account for either the actual outcomes of experimentation or the farmer's initial beliefs about the technology. Thus, the outcomes of some experiments may have made the farmer more optimistic about the technology while the outcomes of others may have made him less so, implying that the coefficients on the past adoption variables are theoretically ambiguous. Second, contem-

poraneous adoption in the network may be signaling something to the farmer about the profitability of the technology, in addition to influencing his behavior through the free-riding and social-pressure channels - this muddies the interpretation of the β coefficients.

Both these limitations can be addressed by directly controlling for the farmer's actual beliefs about the yield of Bt cotton. To do so, I now turn to the main analysis which examines the adoption decisions of farmers in 2008, the point in time at which beliefs about yield were elicited.

Analysis of Adoption Decisions in 2008

Because the analysis now pertains to the planting decision at a single point in time, I drop the t subscripts. I start with the following probit specification:

$$P(y_i = 1) = \Phi(\alpha + \beta(\sum_{-i} y_{-i}) + \gamma\mathbf{\Omega}_i + \delta s_{-i} + \lambda\mathbf{X}_i) \quad (3)$$

where I have slightly abused notation to denote by $\mathbf{\Omega}_i$ the vector of first and second moments of the farmer's belief distribution. The specification differs from that in (2) in the inclusion of the controls for the farmer's beliefs about the yield of Bt and non-Bt cotton and the biosafety concerns of other villagers, denoted by s_{-i} . The vector \mathbf{X}_i now includes input and output prices, the farmer's subjective risk assessment, credit constraints, expected number of pesticide sprays, own biosafety concerns s_i (which may be affected by the number of current adopters in one's network) and village fixed effects.¹²

Table 8 reports the estimated average marginal effects. As before, I estimate the specification in (3), and then refine the network variables further, first differentiating between progressive and non-progressive networks, then differentiating between learning and non-learning networks, and finally considering the most detailed specification.

Adoption in the full network has a statistically significant and positive effect on farmer i 's probability of adoption (column 1), indicating that, on average, the social pressure channel dominates any strategic delays. However, this overall effect disguises the fact that adoption in the progressive network reduces farmer i 's probability of adoption by 6.4 percentage points whereas adoption in the non-progressive network increases the probability of adoption by 0.3 percentage points (column 2), suggesting that free-riding behavior is indeed activated but only by adoption in the progressive network. Distinguishing between learning and non-learning networks (column 3), we find that adoption in the former does indeed reduce farmer i 's probability of adoption by 4.1 percentage points, consistent with strategic delays, while adoption in the non-learning network increases the adoption probability of the farmer by 0.4 percentage points, consistent with the social pressure channel. As expected, the difference $\beta^L - \beta^{nL}$ is negative and statistically significant: The implied strategic delay is that an extra adopter in the learning network reduces the probability of adoption by 4.5 percentage points. Finally, the results from the detailed specification confirm that free-riding behavior is activated by adoption in the progressive learning network, as evidenced by the fact that $\beta^{PF,L} - \beta^{PF,nL}$ is negative and statistically significant, but there is little evidence of free-riding on the experimentation of non-progressive farmers, as evidenced by the fact that $\beta^{nPF,L} - \beta^{nPF,nL}$ is not significantly different from zero. Overall, these results are qualitatively consistent with those obtained in the previous section (Table 7): Notably, however, the point estimates in Table 8 indicate significantly larger free-riding effects than those obtained in Table 7. In particular, an extra adopter in the progressive farmer learning network implies a reduction in the probability of adoption by 30 percentage points. While this is an admittedly large effect, the associated confidence

interval implies that the effect may be as small as 8.7 percentage points. It might also be useful to recall that the number of progressive farmers in each village is small compared to the population as a whole. For instance, in Aurepalle, there are 28 progressive farmers out of a population of 925 households, and farmers, on average, have a 0.3 probability of having a learning link with a given progressive farmer.

In a supplementary appendix online, I present two extensions addressing concerns of endogenous group formation (farmers who are particularly interested in Bt cotton may seek out and form informational links with farmers who plan to cultivate Bt cotton) and simultaneity of actions (of which both strategic delay and social pressures are examples). I find that the results in this section are robust to these extensions.

Discussion

This article takes a closer look at the role of social networks in technology adoption, in the context of the adoption of Bt cotton, a new type of (genetically engineered) cotton available on the Indian market since 2002. To do so, I collected unique data on cotton farmers in three villages in India.

The article makes two contributions. First, I show that social learning appears to have a hierarchical nature, in the sense that farmers in the study villages tend to learn from the experimentation of a select group of progressive farmers, but not from the experimentation of ordinary network neighbors. That is, even though, for most farmers, the conditions in which they operate (in terms of soil and irrigation) might be quite different from the conditions under which the progressive farmers work, they are still more likely to learn from these progressive farmers' experiences than from each others' experiences. This is a surprising finding that adds significant nuance to our understanding of social learning in

rural settings. The policy implications of this finding are also surprising: Given that progressive farmers are central information sources, it might be natural to assume that they should be preferentially targeted with subsidies. In fact, however, the intuition of Bala and Goyal (1998) suggests that in some instances, it might not be a good idea to target progressive farmers: If the technology's performance is variable, then the network structure of who-learns-from-who becomes important. If (as appears to be the case in the study villages) most people learn from observing the experiences of a few influential farmers, then there is an equilibrium in which eventually no one adopts the technology (this occurs if the experimentation by the progressive farmers turns up some bad experiences). In this situation, it may actually make sense to target (perhaps smaller) subsidies to a larger set of individual farmers so as to reduce their reliance on the experimentation of progressive farmers. It should be noted, though, that at least in the Indian setting, the no-adoption scenario has not emerged: Instead, by mid-2000, the all-India adoption rate stood at 80% (as percent of cotton farmers) (Chaudhary and Gaur 2007), and by 2015, 93% of the cotton area was under Bt cotton cultivation (Department of Agriculture and Cooperation, 2015).

Second, GM crops are often associated (rightly or wrongly) with adverse health and environmental effects: The case of Bt cotton is particularly interesting because farmers in rural India - at the time of the survey (in 2008) - appear to have concerns about the effects of the crop on livestock and the environment. Both qualitative as well as quantitative analyses indicate that biosafety concerns are an important determinant of adoption in the study villages. While these concerns might decrease adoption in and by itself, they also give rise to social pressures that inhibit adoption, and as a result, reduce the total information generated about the technology. From a policy perspective, If social pressures are signif-

icant, providing information to a few selected farmers is unlikely to result in wide-scale adoption. Instead, a group-based approach should be used in which farmers can discuss their concerns about the technology and learn about the (lack of) concerns of others. However, because social pressures in this setting relate to the GM nature of the technology, the results of this study cannot be readily extended to other technologies (even though they might be of use to gain an understanding of the adoption process of new GM crops India and other developing countries plan to introduce, such as Bt eggplant). Nevertheless, the method proposed could be adapted to study other technologies (such as, health technologies) where social norms and pressures are suspected to matter.

References

- Abedullah, Kouser, S., and M. Qaim. 2015. "Bt Cotton, Pesticide Use and Environmental Efficiency in Pakistan." *Journal of Agricultural Economics*, 66(1): 66-86.
- Appadurai, A. 1989. "Transformations in the Culture of Agriculture." In C.M. Borden, ed. *Contemporary Indian Tradition: Voices on Culture, Nature and the Challenge of Change*. . Washington and London: The Smithsonian Institution Press, pp. 173-186.
- Bala, V., and S. Goyal. 1998. "Learning from Neighbours." *The Review of Economic Studies*, 65(3): 595-621.
- Bandiera, O., and I. Rasul. 2006. "Social Networks and Technology Adoption in Northern Mozambique." *Economic Journal*, 116(514): 869-902.
- Bantilan, M.C.S., P. Anand Babu, G.V. Anupama, H. Deepthi, and R. Padmaja. 2006. "Dryland Agriculture: Dynamic Challenges and Priorities." Research Bulletin No. 20, GT-IMPI, ICRISAT.
- Besley, T., and A. Case. 1993. "Modeling Technology Adoption in Developing Countries." *American Economic Review*, 83(2): 396-402.
- Chaudhary, B. , and K. Gaur. 2010. "Bt Cotton in India: A Country Profile." *ISAAA Series in Biotech Crop Profiles*. pp. 25.
- Conley, T.G., and C. Udry. 2001. "Social Learning through Networks: The Adoption of New Agricultural Technologies in Ghana." *American Journal of Agricultural Economics, Papers and Proceedings*, 83(3): 668-73.
- Conley, T.G., and C. Udry. 2010 "Learning About a New Technology: Pineapple in Ghana." *American Economic Review*, 100(1): 35-69.
- Delavande, A., Giné, X., and D. McKenzie. 2010. "Eliciting Probabilistic Expectations

with Visual Aids in Developing Countries: How Sensitive are Answers to Variations in Elicitation Design?" *Journal of Applied Econometrics*, 26(3): 479-497.

Delavande, A., Giné, X., and D. McKenzie. 2011. "Measuring Subjective Expectations in Developing Countries: A Critical Review and New Evidence." *Journal of Development Economics*, 94 (2): 151-163.

Department of Agriculture and Cooperation 2014-15. *Annual Report.*, Ministry of Agriculture, Government of India. pp.188.

Duflo, E., Kremer, M., and J. Robinson. 2011. "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya." *American Economic Review*, 101(6): 2350-90.

Feder, G., Just, R., and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change*, 32(2): 255-97.

Feder, G. and S. Savastano. 2006. "The Role of Opinion Leaders in the Diffusion of New Knowledge: The Case of Integrated Pest Management." *World Development*, 34(7): 1287-300.

Foster, A. D., and M.R. Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy*, 103(6): 1176-209.

Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, 25(4): 501-522.

Goyal. S. 2005. "Learning in networks," in G. Demange and M. Wooders, eds. *Group Formation in Economics*. Cambridge: Cambridge University Press, pp. 122—168.

Hogset, H. and C.B. Barrett. 2010. "Social Learning, Social Influence, and Projection

Bias: A Caution on Inferences Based on Proxy Reporting of Peer Behavior," *Economic Development and Cultural Change*, 58(3): 563-589.

Hubbell, B. J., Marra, M.C., and G.A. Carlson. 2000. "Estimating the Demand for a New Technology: Bt Cotton and Insecticide Policies." *American Journal of Agricultural Economics*, 82 (1): 118-32.

ISAAA (International Service for the Acquisition of Agri-Biotech Applications). 2005. *The Story of Bt Cotton in India* - Video.

Kathage, J., and M. Qaim. 2012. "Economic Impacts and Impact Dynamics of Bt (*Bacillus thuringiensis*) Cotton," *Proceedings of the National Academy of Science*, 109(29):11652-11656.

Klumper, W., and M. Qaim. 2014. "A Meta-Analysis of the Impacts of Genetically Modified Crops." *Plos ONE* 9(11): 7.

Krishna, V., Qaim, M., and D. Zilberman. 2014. "Trangenic Crops, Production Risks, and Agrobiodiversity." ZEF-Discussion Papers on Development Policy No 186. pp. 32.

Kouser, S., and M. Qaim. 2011. "Impact of Bt Cotton on Pesticide Poisoning in Smallholder Agriculture: A Panel Data Analysis." *Ecological Economics*, 70(11): 2105-2113.

Lybbert, T. J. and D. R. Just. 2007. "Is Risk Aversion Really Correlated with Wealth? How Estimated Probabilities Introduce Spurious Correlation " *American Journal of Agricultural Economics*, 89(4): 839-1224.

Lu, Y. , Wu, K., Jiang, Y., Guo, Y. and N. Desneux. 2012. "Widespread Adoption of Bt Cotton and Insecticide Decrease Promotes Biocontrol Services." *Nature*, 487: 362-367.

Lu, Y., Wu,K., Jiang, Y., Xia, B., Li, P., Feng, H., Wyckhuys, K.A.G, and Y. Guo. 2010. "Mirid Bug Outbreaks in Multiple Crops Correlated with Wide-Scale Adoption of Bt Cot-

ton." *Science*, 328: 1151-1154.

Maertens, A., and C.B. Barrett. 2013. 'Empirical Methods for Identifying Social Network Effects on Technology Adoption.' *American Journal of Agricultural Economics Papers and Proceedings*, 95(2):353-359

Manski, C. F. 1993. "Identification of Social Interaction: The Reflection Problem." *Review of Economic Studies*, 60:3: 531–542.

Marvier, M., McCreedy, C., Regetz, J., and P. Kareiva. 2007. "A Meta-Analysis of Effect of Bt Cotton and Maize on Nontarget Invertebrate." *Science*, 316: 1475-1477.

McNiven, S.C., and D.O. Gilligan. 2012. "Networks and Constraints on Diffusion of a Biofortified Agricultural Technology: Evidence from a Partial Population Experiment." Mimeo.

Mendelsohn, M., Kough, J., Vaituzis, Z., and K. Matthews. 2005. "Are Bt Crops Safe?" *Nature Biotechnology*, 21(5): 1003-09.

Moser, C.M., and C.B. Barrett. 2006. "The Complex Dynamics of Smallholder Technology Adoption: The Case of SRI in Madagascar." *Agricultural Economics*, 35(3): 373–388.

Munshi, K. 2004. "Social Learning in a Heterogenous Population: Technology Diffusion in the Indian Green Revolution," *Journal of Development Economics*, 74(1): 175-213.

Pemsl, D., H. Waibel, and J. Orphal. 2004. "A Methodology to Assess the Profitability of Bt-cotton: Case Study Results from the State of Karnataka, India " *Crop Protection*, 23(12):1249-57.

Qaim, M., and D. Zilberman. 2003. "Yield Effects of Genetically Modified Crops in Developing Countries." *Science*, 299(7): 900-902.

Qaim, M. 2003. "Bt Cotton in India: Field Trial Results and Economic Projections."

SOCIAL LEARNING AND SOCIAL PRESSURES IN COTTON FARMING

World Development, 31:12: 2115–27.

Rao, K.P.C. and Kumara D. Charyulu. 2007. "Changes in Agriculture and Village Economies." *Research Bulletin* no 21, GT-IMPI, ICRISAT.

Rogers, E. 1962 and 1995. *Diffusion of Innovations*. New York: Free Press.

Santos, P., and C. B. Barrett. 2007. "Understanding the Formation of Social Networks." Mimeo.

Shelton, A. M., J.-Z. Zhao, and R. T. Roush. 2002. "Economic, Ecological, Food Safety and Social Consequences of the Deployment of Bt Transgenic Plants." *Annual Review of Entomology*, 47: 845-81.

Sunding, D., and D. Zilberman. 2001. "The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector," in B.L. Gardner and G.C. Rausser eds., *Handbook of Agricultural Economics*. Elsevier Science, pp. 207-61.

Tabashnik, B.E., T. Brevault, and Y. Carriere. 2013. "Insect Resistance to Bt Crops: Lessons from the First Billion Acres." *Nature*, 31(6): 510-521.

United States Department of Agriculture, 2016. *Production, Supply and Distribution On-line Dataset*. Available from <http://apps.fas.usda.gov/psdonline/>

Vasavi, A. R. 1994. "Hybrid Times, Hybrid People': Culture and Agriculture in South India." *Man*, 29(2): 283-300.

Walker, T.S., and J. G. Ryan. 1990. *Village and Household Economies in India's Semi-Arid Tropics*. Baltimore and London: John Hopkins University Press.

Qiao, F. 2015. "Fifteen Years of Bt Cotton in China: The Economic Impacts and its Dynamics." *World Development*, 70: 177-185.

Notes

¹A notable exception is Duflo, Kremer and Robinson (2011) who, using a randomized intervention, cannot find evidence of social learning about fertilizer use in Kenya.

²The Bt cultivars contain a gene sourced from the soil bacterium *Bacillus thuringiensis*, which produces a protein that is toxic to bollworms, but provides no protection against other pests and diseases. When a Bt gene is inserted in the DNA of a plant it only affects its pest resistance. It does not affect its duration, drought resistance, or fiber length, etc. These properties are determined by the genetic properties of the cultivar in which the gene is inserted. In effect, whether or not a farmer adopts Bt cotton is likely to depend on the availability of local cultivars with the Bt gene. Krishna et al. (2014) note that, over time, "the availability of many local varieties helped farmers to preserve diversity even with full Bt adoption" (p. 18). See Choudhary and Gaur (2010) for an overview of the Bt cultivars on the Indian market.

³These rates refer to the Bollgard-I variety of Monsanto.

⁴However, if the bollworm pressure is low (and hence fewer pesticides are needed) and the price of the Bt seed is high this result might not hold. Pemsil, Waibel and Orphal (2004), using farm data from non-isogenic Bt and non-Bt cultivars during 2002-03, a low bollworm pressure year, conclude that, irrespective of soil and climatic conditions, non-Bt cotton outperforms Bt cotton.

⁵The respondent was asked whether he would consider input credit and whom he could ask/where he could go if he ever wanted to obtain credit for inputs, and how likely it would be he would received credit from this source.

⁶I elicited a self-assessed estimate of willingness to take on risks (using a Likert scale). See a supplementary appendix online.

⁷I first elicited the minimum and maximum yield (per acre) of two Bt and non-Bt cultivars of the respondent's choice conditional on the respondent's soil characteristics, irrigation status and expected input use. Then, I made five boxes, evenly distributed between this minimum and maximum and I asked the respondent to use 20 stones (each stone representing a 5% probability) to form a yield density function. After each yield distribution game, I asked the respondent how much he expects to pay i) for the seed (per acre), and ii) for pesticides and for other inputs (per acre). The respondents understood the yield distribution game very well,

SOCIAL LEARNING AND SOCIAL PRESSURES IN COTTON FARMING

as it was narrated in a way farmers in these regions think about their yields, making reference to the weather variability and pest pressure variability. In the analysis, I average the information of both Bt (non-Bt) cultivars.

⁸Specifically, the questions read "Bt cotton is hazardous for animal health: They might get sick or die when they eat the fodder" ; "Bt cotton is hazardous for human health: If you touch it too much, you might get sick"; and "Bt cotton is hazardous for the environment: It damages other crops and soils." Note that no explicit reference is made to reduced pesticide use and the potential effects of this on health and the environment. Each of these three questions has five possible answers, ranging from 'strongly disagree' to 'strongly agree' and a 'don't know' option.

⁹I do not use yield data from 2007-2008 because these are extremely noisy, possibly due to the fact that the Maharashtra villages experienced significant flooding during this year.

¹⁰These figures are based on the entire sample of 43 progressive farmers, which includes 21 farmers who were not part of the ICRISAT-VLS sample.

¹¹After this point, his adoption decision starts to depend on his own prior experimentation, which introduces a lagged dependent variable as a regressor. Because of the difficulties in obtaining unbiased estimates in such models, I truncate the sample at first adoption. The results for the non-truncated sample, controlling for own prior experimentation are nevertheless quite similar - see Table 3 in the supplementary appendix online.

¹²I do not include as controls productive characteristics such as education and access to irrigation, as these are already embedded in the yield beliefs.

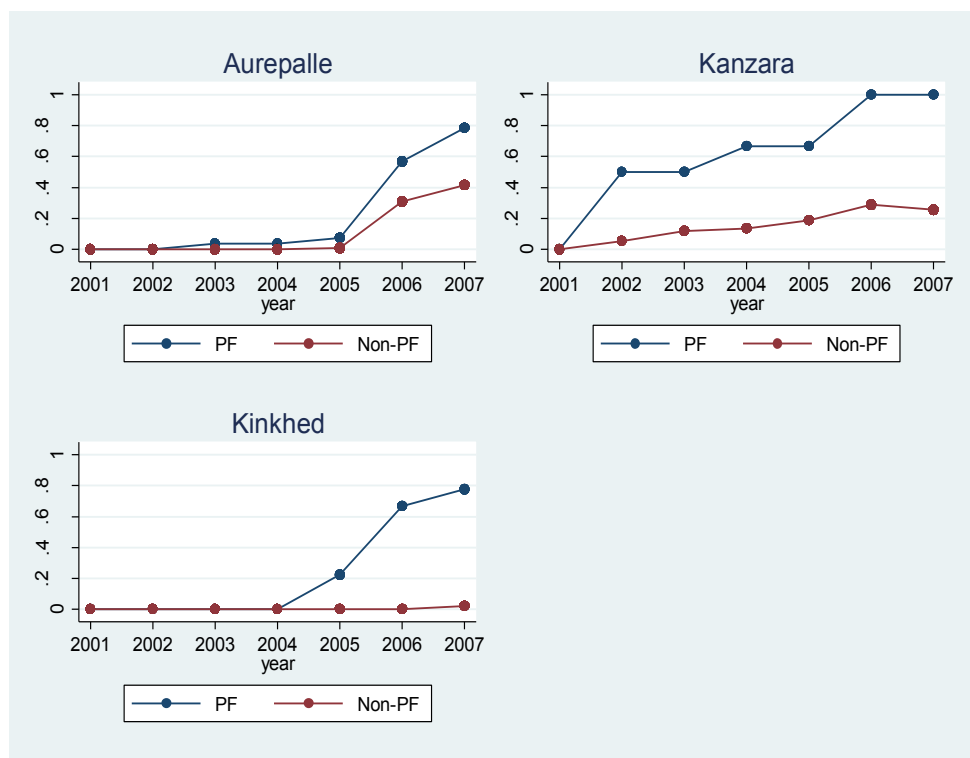


Figure 1. Bt Cotton Adoption over Time in the Study Villages

Note: The panels above show the adoption rate of Bt cotton over time for each of the three study villages, separately for progressive (PF) and non-progressive (non-PF) farmers. These rates are based on retrospective information on adoption provided by the respondents and include all progressive farmers in the survey sample (including those who were not in the original ICRISAT-VLS sample). The difference between progressive and non-progressive farmer rates of adoption is statistically significant at the 5% level (i) from 2006 onwards in Aurepalle, (ii) from 2002 onwards in Kanzara and (iii) from 2005 onwards in Kinkhed.

Table 1. Cotton Farmer Characteristics in 2008

	Aurepalle		Kanzara		Kinkhed		All villages		Diff (PF-non-PF)
	PF	non-PF	PF	non-PF	PF	non-PF	PF	non-PF	
Number of household members	4.50 (2.47)	3.30 (1.22)	4.00 (1.00)	4.35 (1.27)	3.83 (1.17)	3.39 (1.34)	4.24 (1.97)	3.51 (1.31)	0.72** (0.34)
Education level of farmer (in years)	2.92 (2.97)	2.28 (3.76)	10.00 (4.00)	6.00 (3.13)	11.33 (1.97)	6.86 (3.29)	6.33 (4.89)	4.14 (4.10)	2.20** (1.01)
Annual income (in thousands of Rs)	103.93 (51.85)	58.42 (38.09)	234.77 (184.21)	100.75 (146.93)	61.71 (36.40)	45.25 (49.69)	110.56 (90.88)	62.81 (74.69)	47.75** (18.46)
Owned irrigated land (acres)	4.22 (3.03)	1.05 (1.62)	19.75 (2.95)	2.84 (5.20)	15.46 (8.60)	1.70 (2.40)	9.65 (8.22)	1.54 (2.85)	8.11*** (0.99)
Owned dry land (acres)	5.27 (4.04)	3.33 (2.55)	0.00 (0.00)	3.45 (4.22)	5.71 (5.70)	3.46 (5.55)	4.64 (4.57)	3.38 (3.80)	1.26 (0.94)
Consider obtaining input credit? ^a	1.00 (0.00)	0.92 (0.28)	1.00 (0.00)	0.9 (0.31)	0.5 (0.55)	0.44 (0.51)	0.86 (0.36)	0.79 (0.41)	0.06 (0.10)
Subjective risk assessment ^b	4.58 (0.51)	3.03 (0.82)	4.33 (0.58)	2.85 (1.09)	4.5 (0.55)	3.14 (1.08)	4.52 (0.51)	3.03 (0.94)	1.50*** (0.21)
Number of observations	12	61	3	20	6	28	21	109	

Notes: The table summarizes the socio-economic characteristics of the cotton farmers in the study sample in each of the three study villages, distinguishing between progressive (PF) and non-progressive (non-PF) farmers. ^aThis is a binary response to the question of whether the farmer would consider obtaining credit to purchase inputs (yes=1; no=0).

^bSubjective risk assessment corresponds to the answer to the question: "Compared to others, do you think that you take: Much less risks (1); Somewhat less risks (2); About the same risks (3); Somewhat more risks (4); Much more risks (5)." Standard deviations are in parentheses. The last column reports differences between progressive and non-progressive farmers in the full sample, along with associated standard errors in parentheses. The asterisks denote statistical significance of these differences, based on t-tests. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Biosafety Concerns among Cotton Farmers in 2008

	Aurepalle		Kanzara		Kinkhed		All villages		
	PF	non-PF	PF	non-PF	PF	non-PF	PF	non-PF	Diff (PF-non-PF)
<i>Bio-safety concerns</i>									
Own (index ranges from 1 to 5)	1.47 (0.69)	1.71 (0.84)	1.33 (0.00)	2.43 (0.72)	2.78 (0.66)	2.80 (0.72)	1.83 (0.87)	2.12 (0.92)	-0.29 (0.17)
Others (index ranges from 1 to 5)	1.53 (0.67)	1.72 (0.79)	2.67 (0.33)	2.85 (0.52)	2.78 (0.66)	2.86 (0.74)	2.05 (0.86)	2.22 (0.92)	-0.17 (0.22)
Number of observations	12	61	3	20	6	28	21	109	130

Notes: The table summarizes the beliefs of the cotton farmers in the sample with respect to the biosafety of Bt cotton. "Biosafety concern of self (others)" is the average of the answers to "To what degree do you yourself think (think other villagers think) that Bt cotton is hazardous for (1) animal health, (2) human health and (3) the environment?". The responses to this question are categorical, and range from 1 to 5, with higher values referring to an increased concern with biosafety issues. Standard deviations in parentheses. The last column reports the differences between progressive and non-progressive farmers in the full sample, along with associated standard errors in parentheses. The asterisks denote statistical significance of these differences, based on t-tests. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Yield Beliefs among Cotton Farmers in 2008

	Aurepalle		Kanzara		Kinkhed		All villages		
	PF	non-PF	PF	non-PF	PF	non-PF	PF	non-PF	Diff (PF-non-PF)
<i>Bt cotton</i>									
<i>1st variety</i>									
Expected yield (Quintal/acre)	9.66 (1.77)	8.72 (1.74)	7.90 (2.33)	6.66 (2.14)	5.84 (0.82)	5.13 (0.94)	8.32 (2.32)	7.42 (2.26)	0.89* (0.54)
Variance of yield (Quintal/acre)	2.22 (1.60)	1.80 (1.02)	3.37 (1.55)	2.81 (1.93)	1.77 (0.30)	1.40 (0.84)	2.26 (1.39)	1.88 (1.88)	0.37 (0.31)
<i>2nd variety</i>									
Expected yield (Quintal/acre)	9.12 (1.72)	8.24 (1.93)	5.83 (1.81)	6.30 (1.99)	5.84 (0.48)	5.87 (1.20)	7.71 (2.19)	7.28 (2.08)	0.44 (0.5)
Variance of yield (Quintal/acre)	1.80 (0.61)	1.35 (0.92)	1.46 (0.77)	1.97 (1.11)	1.78 (0.74)	1.54 (0.79)	1.74 (0.65)	1.52 (0.95)	0.23 (0.29)
<i>Non-Bt cotton</i>									
<i>1st variety</i>									
Expected yield (Quintal/acre)	5.74 (1.34)	5.08 (1.05)	4.90 (1.85)	3.98 (1.01)	3.98 (0.53)	3.42 (0.50)	5.12 (1.42)	4.45 (1.18)	0.66* (0.29)
Variance of yield (Quintal/acre)	0.74 (0.71)	0.62 (0.45)	2.10 (1.71)	0.90 (0.69)	1.33 (0.47)	0.80 (0.68)	1.10 (0.93)	0.72 (0.48)	0.39*** (0.14)
<i>2nd variety</i>									
Expected yield (Quintal/acre)	5.02 (0.95)	4.67 (1.09)	4.09 (1.18)	3.94 (1.27)	4.23 (0.44)	3.67 (0.68)	4.66 (0.93)	4.28 (1.13)	0.38 (0.26)
Variance of yield (Quintal/acre)	0.53 (0.32)	0.55 (0.31)	0.94 (0.61)	0.96 (1.07)	1.26 (0.37)	0.78 (0.34)	0.80 (0.49)	0.68 (0.56)	0.12 (0.13)
Number of observations	12	61	3	20	6	28	21	109	130

Notes: The table summarizes the beliefs of the cotton farmers in the sample with respect to the yield of Bt and non-Bt cotton (beliefs were elicited for two varieties of Bt and non-Bt cotton, respectively), calculated assuming a step-wise distribution with the minimum and maximum of the distribution as specified by the respondent (1 quintal=100kg). Standard deviations in parentheses. The last column reports the differences between progressive and non-progressive farmers in the full sample, along with associated standard errors in parentheses. The asterisks denote statistical significance of these differences, based on t-tests. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Actual Yields among the Sample of 2008 Cotton Farmers Realized in 2006-2007

	Aurepalle		Kanzara		Kinkhed		All villages		
	PF	non-PF	PF	non-PF	PF	non-PF	PF	non-PF	Diff (PF-non-PF)
Bt cotton (quintals/acre)	6.43	4.03	5.36	2.22	2.50		5.58	3.78	1.79**
	(2.43)	(1.66)	(1.54)	(0.92)	(0.71)		(2.44)	(1.69)	(0.61)
Non-Bt cotton (quintals/acre)	4.93	3.92	1.78	2.49	2.64	3.38	2.96	3.09	-0.13
	(2.01)	(1.84)	(0.27)	(1.57)	(2.93)	(2.73)	(2.49)	(2.29)	(0.85)

Notes: The table summarizes the actual yields of the cotton farmers in the sample of 2008 cotton farmers with respect to Bt and non-Bt cotton in 2006-2007. Standard deviations are in parentheses. The last column reports the difference in average yield between progressive and non-progressive farmers in the full sample, along with associated standard errors in parentheses. The asterisks denote statistical significance of these differences, based on t-tests. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Correlates of Expected Yield of Bt Cotton among Cotton Farmers in 2008

<i>Dependent variable: Expected yield of Bt cotton</i>	1st cultivar				2nd cultivar			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Progressive farmer (dummy)	0.937 (0.569)	0.322 (0.602)	-0.610 (0.941)	-0.753 (0.990)	0.362 (0.585)	-0.179 (0.614)	-1.099 (1.004)	-1.276 (1.046)
Education (years)	-0.136** (0.061)	-0.082 (0.056)	-0.091 (0.099)	-0.090 (0.095)	-0.077 (0.060)	-0.029 (0.056)	-0.068 (0.105)	-0.067 (0.100)
Fraction of land irrigated	1.395*** (0.532)	0.626 (0.513)	0.177 (0.647)	0.162 (0.578)	1.300** (0.563)	0.621 (0.538)	0.300 (0.666)	0.248 (0.610)
Cultivated Bt cotton before (dummy)		1.966*** (0.439)				1.733*** (0.403)		
Bt yield in 2006-2007 (quintals/acre)			0.343* (0.175)				0.281* (0.145)	
Bt profit in 2006-2007 (thousands of rupees/acre)				0.265** (0.123)				0.239** (0.105)
Constant	7.779*** (0.327)	6.621*** (0.364)	7.933*** (0.885)	8.717*** (0.564)	7.402*** (0.319)	6.382*** (0.364)	7.695*** (0.791)	8.305*** (0.497)
Observations	130	130	50	50	130	130	50	50
R-squared	0.164	0.302	0.118	0.129	0.101	0.228	0.126	0.148

Notes: The table presents regressions of the expected yield of Bt cotton on farmer characteristics and prior experience with Bt cotton cultivation. In columns 1-4, the expected yield refers to the first cultivar of Bt cotton that the farmer provided beliefs for, while columns 5-8 refer to the expected yield for the second cultivar. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 6. Networks among Cotton Farmers in 2008

	Aurepalle	Kanzara	Kinkhed
Number of farmers whose cultivar is known	4.44 (1.69)	5.74 (1.63)	6.85 (1.94)
Number of farmers whose cultivar, pesticide use and yield are known	1.71 (1.87)	2.22 (2.37)	5.56 (2.60)
Number of progressive farmers whose cultivar is known	2.68 (1.17)	3.83 (0.83)	3.71 (1.38)
Number of non-progressive farmers whose cultivar is known	1.75 (1.75)	1.91 (1.28)	3.15 (1.37)
Number of observations	73	23	34

Notes: The table shows the size of the average individual's network, differentiating between progressive and non-progressive farmers in the network, and between learning and non-learning networks. Network sizes are based on a random-matching-within-sample exercise, in which each respondent was asked about his relationship with and information about (i) 4 progressive farmers, and (ii) 6 non-progressive farmers in the village. Standard deviations in parentheses.

Table 7. Effect of Past and Contemporaneous Adoption in Network

<i>Dependent variable: Indicator for Bt cotton adoption</i>	(1)	(2)	(3)	(4)
<i>Number of current adopters in</i>				
- Full network ($n_{i,t}$)	0.001*** (0.000)			
- PF network ($n_{i,t}^{PF}$)		-0.007* (0.004)		
- Non-PF network ($n_{i,t}^{nPF}$)		0.002*** (0.000)		
- Learning network ($n_{i,t}^L$)			0.000 (0.000)	
- Non-learning network ($n_{i,t}^{nL}$)			0.001*** (0.000)	
- PF learning network ($n_{i,t}^{PF,L}$)				-0.013** (0.006)
- PF non-learning network ($n_{i,t}^{PF,nL}$)				-0.004 (0.004)
- Non-PF learning network ($n_{i,t}^{nPF,L}$)				0.001* (0.001)
- Non-PF non-learning network ($n_{i,t}^{nPF,nL}$)				0.002*** (0.001)
<i>Cumulative number of past adopters in</i>				
- Full network ($n_{i,-t}$)	-0.001* (0.001)			
- PF network ($n_{i,-t}^{PF}$)		0.014** (0.007)		
- Non-PF network ($n_{i,-t}^{nPF}$)		-0.002*** (0.001)		
- Learning network ($n_{i,-t}^L$)			-0.000 (0.001)	
- Non-learning network ($n_{i,-t}^{nL}$)			0.000 (0.000)	
- PF learning network ($n_{i,-t}^{PF,L}$)				0.016*** (0.005)
- PF non-learning network ($n_{i,-t}^{PF,nL}$)				-0.001 (0.003)
- Non-PF learning network ($n_{i,-t}^{nPF,L}$)				-0.002** (0.001)
- Non-PF non-learning network ($n_{i,-t}^{nPF,nL}$)				0.000 (0.001)
Observations	813	813	813	813
$\beta^L - \beta^{nL}$			-0.001* (0.000)	
$\beta^{PF,L} - \beta^{PF,nL}$				-0.009* (0.005)
$\beta^{nPF,L} - \beta^{nPF,nL}$				-0.000 (0.001)

Notes: The table presents the average marginal effects corresponding to probit regressions, in which the dependent variable is an indicator for whether the farmer cultivated Bt cotton in a particular year. The regression sample retains each farmer up to the point of his first adoption. The bottom panel presents the estimated differences between coefficients on adoption in the learning and non-learning networks, along with the estimated standard error in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Controls for information received from non-farmer sources (e.g., seed dealers), the farmer's subjective risk assessment, education level of the decision maker, assets, credit constraints, soil fertility and irrigation constraints, prices, village and year fixed effects. The full set of regression coefficients is reported in the supplemental appendix online.

Table 8. Effect of Contemporaneous Adoption in Network (Main Analysis)

<i>Dependent variable: Indicator for Bt cultivation in 2008</i>				
	(1)	(2)	(3)	(4)
<i>Number of current adopters in</i>				
- Full network (n_i)	0.003*			
	(0.002)			
- PF network (n_i^{PF})		-0.064**		
		(0.028)		
- Non-PF network (n_i^{nPF})		0.003*		
		(0.002)		
- Learning network (n_i^L)			-0.041**	
			(0.019)	
- Non-learning network (n_i^{nL})			0.004***	
			(0.002)	
- PF learning network ($n_i^{PF,L}$)				-0.299**
				(0.140)
- PF non-learning network ($n_i^{PF,nL}$)				0.009
				(0.049)
- Non-PF learning network ($n_i^{nPF,L}$)				0.001
				(0.068)
- Non-PF non-learning network ($n_i^{nPF,nL}$)				0.005**
				(0.002)
Observations	128	128	128	128
$\beta^L - \beta^{nL}$			-0.045**	
			(0.019)	
$\beta^{PF,L} - \beta^{PF,nL}$				-0.308***
				(0.112)
$\beta^{nPF,L} - \beta^{nPF,nL}$				-0.004
				(0.067)

Notes: The table presents average marginal effects corresponding to probit regressions, in which the dependent variable is an indicator for whether the farmer had decided to cultivate Bt cotton in the 2008 cultivation period. The bottom panel presents the estimated differences between coefficients on adoption in the learning and non-learning networks, along with the estimated standard error in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. Controls for input and output prices, the farmer's subjective risk assessment, credit constraints, expected number of pesticide sprays, own and others' bio-safety concerns, and village fixed effects. The full set of regression coefficients is reported in the supplemental appendix online.